Poster 15: Exploring Sentinel-1 and Sentinel-2 diversity for Flood inundation mapping using deep learning

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Motivation

Identification of flood water extent from satellite images has historically relied on either synthetic aperture radar (SAR) or multi-spectral (MS) imagery. But MS sensors may not penetrate cloud cover, whereas SAR is plagued by operational errors such as noise-like speckle challenging their viability to global flood mapping applications. An attractive alternative is to effectively combine MS data and SAR, i.e., two aspects that can be considered complementary with respect to flood mapping tasks. Therefore, in this study, we explore the diverse bands of Sentinel 2 (S2) derived water indices and Sentinel 1 (S1) derived SAR imagery along with their combinations to access their capability in generating accurate flood inundation maps using a fully connected deep convolutional neural network known as U-Net.

Data

For this study, we use a new georeferenced flood label data i.e. Sen1Floods11 (Bonafiell et al., 2020) which provides flood inundation labels spanning over 11 flood events across the world (Table 1, Figure 1). This dataset contains human supervised flood labels generated for 446 images at 10-meter resolution at 512×512 dimensions. The dataset further provides corresponding S1 and S2 bands for the labeled flood events. For our study, we only use all the 446 human supervised images for deep learning model evaluation.

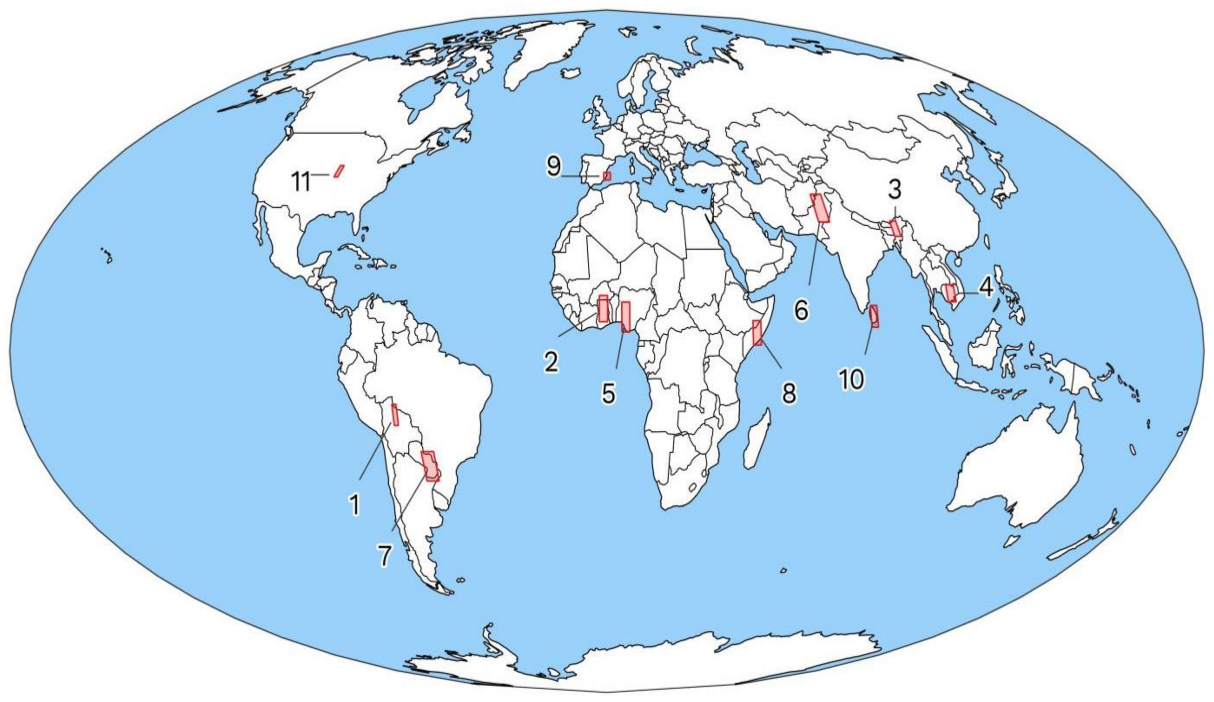

Figure 1:Locations of flood events sampled in Sen1Floods11

Table 1: Flood event acquisition time in Sen1Floods11

ID	Country	S2 Date	S1 Date
1	BOLIVIA	2/15/2018	2/15/2018
2	GHANA	9/19/2018	9/18/2018
3	INDIA	8/12/2016	8/12/2016
4	VIETNAM	8/4/2018	8/5/2018
5	NIGERIA	9/20/2018	9/21/2018
6	PAKISTAN	6/28/2017	6/28/2017
7	PARAGUAY	10/31/2018	10/31/2018
8	SOMALIA	5/5/2018	5/7/2018
9	SPAIN	9/18/2019	9/17/2019
10	SRI LANKA	5/28/2017	5/30/2017
11	USA	5/22/2019	5/22/2019

U-Net

We use a variation of Convolutional neural network architectures called as U-Net for flood identification. U-Net has been referred to as having an effective structure to successfully perform image segmentation tasks (Ronneberger et al., 2016). Firstly, the encoder half of the model carries out a downsampling process, bringing the input image down to small size feature matrix (Figure 2). Secondly, the decoder constructs the model output using the features as input and carries out an upsampling process to bring back the spatial information of input image

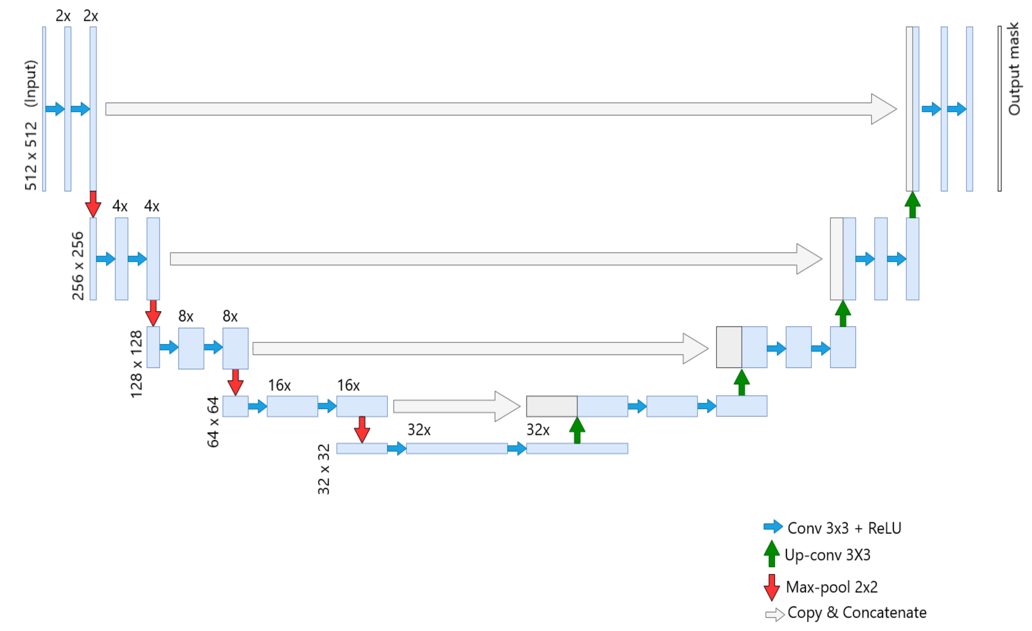

Figure 2: Pictorial representation of U-net architecture adopted for segmentation of water extents

Experimental setup & evaluation criteria

The 446 images used in this study are divided randomly into splits containing 70 % of images for training, 20 % for validating and 10 % for testing. Several possible combinations were tested. For all the combinations, a separate set of experiments with DEM as an additional input to combination bands of S-1 and S-2 were also run. Firstly, in case of S1, we use both VV/VH bands to establish benchmark performance of S-1 for flood inundation mapping. In case of S-2, the combined spectral indices of NDVI and MNDVI (cNDVI), $AWEI_{sh}$ and $AWEI_{nsh}$ (cAWEI) and their combination as input to our deep learning algorithm. Also, HSV bands and their combination with spectral indices were used in our experiment. Finally, all S-2 band configurations are combined with S-1 to evaluate S-1 and S-2 combinations. Precision, recall and their harmonic mean (F1 Score) were used to evaluate combinations (Figure 3).

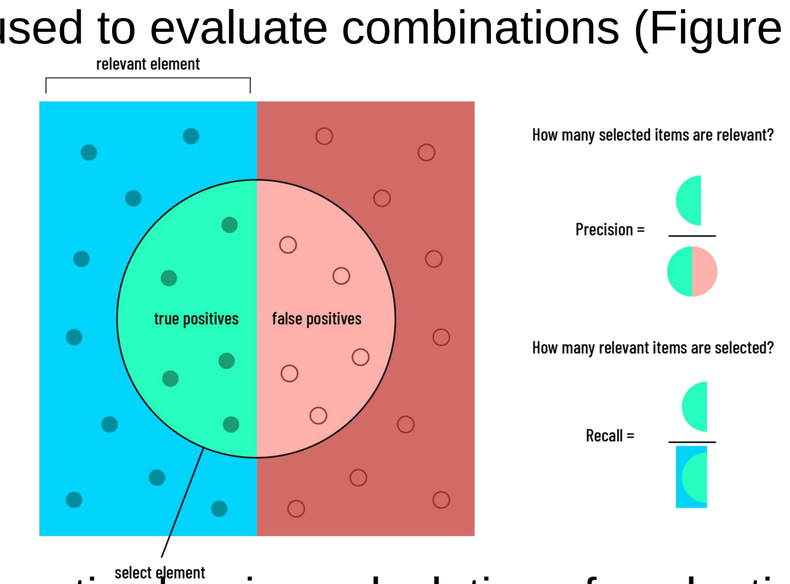

Figure 3:Schematic showing calculation of evaluation metrics

Results

Impact of DEM on S1

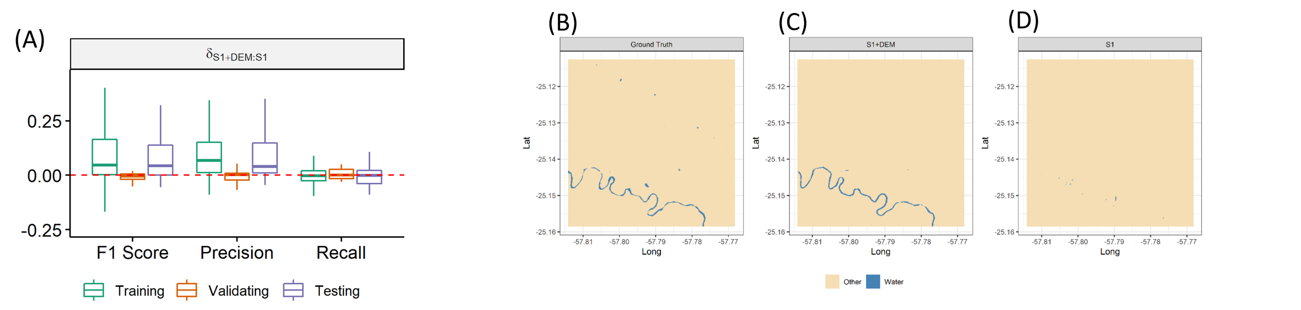

Figure 4: The fractional difference between performance of S1 bands+DEM and S1 is shown in (A). Flood inundation of a location in Paraguay based on ground truth(B), produced by U-Net when using (C) S1+DEM as input and (D) HSV + DEM as input.

Difference in performance between S2 and S1

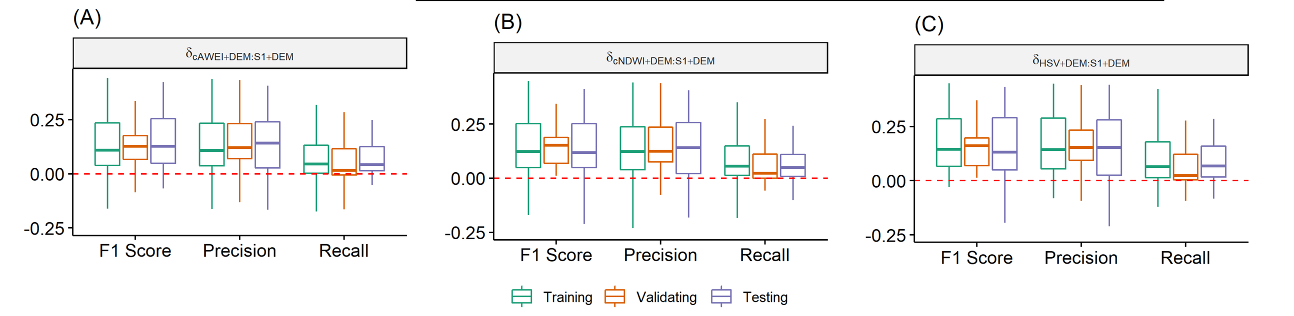

Figure 5: Boxplots representing the fractional difference between (A) cAWEI+DEM (B) cNDWI+ DEM (C) HSV +DEM and S1+DEM.

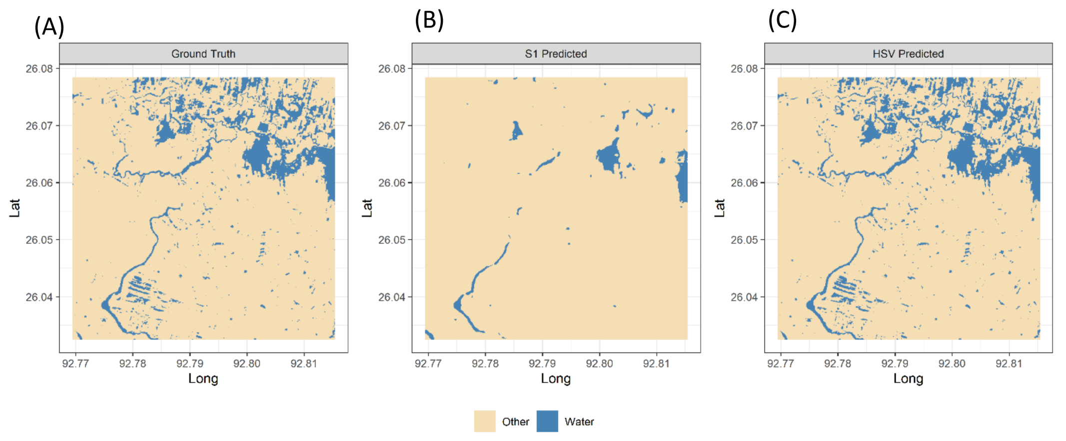

Figure 6: Flood inundation of a location in India based on ground truth(A), produced by U-Net when using (B) S1+DEM as input and (C) HSV + DEM as input.

Performance change between S1+S2 and S2

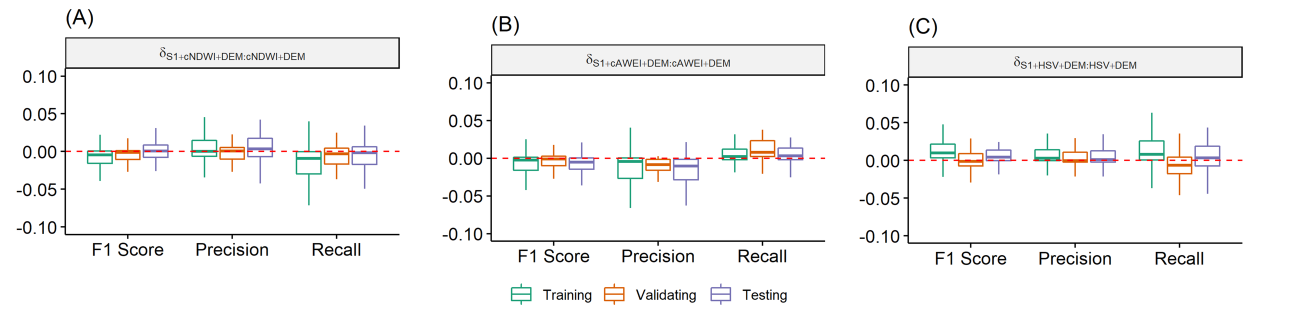

Figure 7: Boxplots representing the fractional difference in performance between (A) S1+cNDWI+DEM and cNDWI+DEM, (B) S1+cAWEI+DEM and cAWEI+DEM (C) S1+HSV+DEM and HSV+DEM

Performance improvement of between S1+S2 over MODIS NRT

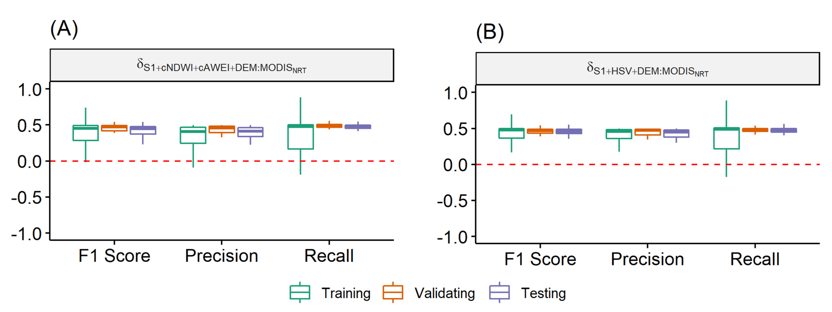

Figure 8: Boxplots representing the fractional difference in performance between (A) S1+cAWEI+cNDWI+DEM (B) S1+HSV +DEM and MODIS NRT

Summary:

- Our results indicated that even though the SAR data is not affected by cloud cover, poor contrast between VV and VH backscatter has affected S1 data's flood inundation mapping performance.
- The trained U-net was able to achieve a median F1 score of 0.74 when using DEM and S1 bands as input in comparison to 0.63 when using only S1 bands highlighting the active positive role of DEM in mapping floods.
- Among the S2 bands, HSV (Hue, Saturation, Value) transformation of Sentinel 2 data has achieved a median F1 score of 0.91 outperforming the commonly used water spectral indices owing to HSV's transformation's superior contrast distinguishing abilities.
- Also, the U-Net algorithm outperforms the MODIS NRT products by around 50%.

References:

Bonafilia, D., Tellman, B., Anderson, T., & Issenberg, E. (2020). Sen1Floods11: a georeferenced dataset to train and test deep learning flood algorithms for Sentinel-1. 2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), 835-845.

O. Ronneberger, P. Fischer and T. Brox, "U-net: Convolutional networks for biomedical image segmentation", *Proc. Int. Conf. Med. Image Comput. Comput.-Assist. Intervent. (MICCAI)*, pp. 234-241, 2015.

Konapala G., Kumar S.V., Ahmed S., Exploring Sentinel-1 and Sentinel-2 diversity for Flood inundation mapping using deep learning, (In review)